Time Constraints and the Quality of Physician Care

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July, 2023

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Abstract

This paper studies how time constraints affect the quality of physician care. Insufficient examination time may hamper physicians' care and diagnostic provision, leaving physicians more inclined to over-prescribe medication. I test this prediction using high-frequency data from a Spanish outpatient department and leverage on-the-day cancellations as random time shocks. I find that longer visits lead to better care, measured by providing more detailed diagnoses, higher testing intensity, and lower drug prescriptions. These effects are driven by junior physicians, who use this extra time to compensate for their more overloaded shifts.

Keywords: Healthcare productivity, quantity-quality trade-off, contracts, decision-making

JEL Classification: H0; I0; J0

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1 Introduction

Working under time pressure has become a hallmark of today's economy. According to a survey conducted by Eurofound (2017), 36% of the workers in the European Union work under tight deadlines, while 10% report needing more time to complete their tasks.[1] Time pressure is most critical for the healthcare industry, where accurate and timely decision-making might prevent long-lasting social costs. Despite that, 14% of healthcare workers report not having the minimum time required to do their job correctly while also being the sector most affected by high emotional demands. In this context, it is vital to understand how time constraints affect health care decisions. However, little is known in that respect.

In this paper, I investigate how the time physicians spend reviewing patients causally affects the quality of the physician care and the treatment provided, using detailed high-frequency information from a Spanish outpatient department. I focus on the provision of a detailed diagnosis as a proxy for a visit's successful completion, given that outpatient physicians' job is to provide clear-cut advice to those patients referred from Primary Care Centers. I also examine several other health care decisions and outcomes, including the number of tests ordered and their corresponding cost, the number of drugs prescribed, whether patients have subsequent visits, and the likelihood that either patients or physicians cancel those visits.

The main empirical challenge to estimating the causal effect of visit length on physicians' decisions is to obtain a relevant source of time that is also exogenous to the patient's characteristics. I address that challenge by leveraging on-the-day cancellations as random time shocks to the physicians' schedules. When a cancellation occurs, physicians generally spend more time with all the visits for the remainder of the shift but also provide the very next scheduled visit with an unexpected extra visit length. I focus on such *bonus* time to extract conclusions on how physicians' diagnostic behavior responds to an unexpected increase in consultation time. This random time shock is essential as otherwise, physicians, having a complete picture of their shifts, could decide to provide more extended visits based on patients' characteristics. On-the-day cancellations represent 15% of all visits.

A second obstacle that might hinder our causal estimation is the physicians' prioritization of patients with specific characteristics once a cancellation occurs. While physicians have to follow their daily schedule by law, in practice, they might select which patients to treat when a slot is freed. To tackle that concern, I focus only on first visits to the outpatient

[1] By comparison, in 1991, only 23% of the European Union workers worked under tight deadlines (Eurofound, 1993).

department, as new patients have no prior contact with their treating physician, minimizing such selection. Moreover, the Spanish outpatient system prevents patients from strategically responding to physician's cancellations by forbidding in-office dropouts and on-the-day appointments.

I build a unique dataset containing the universe of visits to a Spanish outpatient department between 2016 and 2018 and complement it with high-frequency information on the physician's schedules and the treatments and diagnoses provided. The main specification uses an IV approach, instrumenting the time allocated to review each patient with whether the prior scheduled visit got canceled. I include physician fixed effects to control for inherent physicians' characteristics, and by construction, by those of their specializations; month-by-year fixed effects to control for seasonality confounders; hour fixed effects to account for different hour-patient compositions; and a comprehensive set of controls for patients' characteristics.

I find that longer visits increase the likelihood of providing a diagnosis, which is the main objective of outpatient departments. For every extra minute of examination, the likelihood of providing a diagnosis increases by 4%. This effect is driven by uncommon diagnoses, while no effect is found on the most common diagnoses, suggesting that longer visits allow physicians to review patients in more detail and provide them with a higher-value service. Longer first visits also increase diagnostic input utilization in the form of procedures and laboratory tests, and decrease drug prescriptions. For every extra minute used to review patients, physicians provide 3% more tests, increasing the overall testing cost by 6%, and reduce the drug doses prescribed by 20%. These results suggest that test ordering, especially more expensive tests, complements longer visits, while drug prescription is used as a substitute for insufficient reviewing time. Overall, physicians use the extra visiting time to assess the patient's health problems in more detail, and in the event of indecision, to request further diagnostic inputs, ultimately improving the service provided.

I then look at how physicians' contracts influence diagnostic provision. These contracts, based on seniority, provide senior physicians with less overloaded shifts at the expense of their junior colleagues. I find that longer visits only lead to changes in the input composition and the provision of a diagnosis when such extra time is provided to junior physicians. In contrast, the extra time does not affect senior physicians. While junior and senior physicians react to cancellations by providing more time to their subsequent patients, only junior physicians use the additional time to promote a service of higher quality. With these results in mind, I provide a back-of-the-envelope calculation for the direct labor cost of increasing diagnosis rates. Policymakers could attempt to improve diagnostic rates by increasing every physician's visiting times across the board. However, doing so might prove inefficient, as it does not internalize that senior physicians' practices are unaffected by longer visit lengths. A tailored approach targeting only junior physicians might help improve health provision while minimizing expenditure.

Understanding the trade-off between time and employee productivity is essential from a policy perspective. On the one hand, the provision of longer visits comes at the expense of fewer visits per shift and, in equilibrium, of longer waiting lists to access the outpatient department. On the other hand, longer visits lead to higher visit quality, improving patients' health outcomes and reducing their need for readmission. To the best of my knowledge, this paper is the first to provide causal evidence that longer reviewing time improves visit quality and show that correcting the distortionary incentives created by seniority-based contracts may be welfare-improving.

This paper contributes to different strands of the literature. First, it complements the growing literature on the determinants of physicians' labor supply. Recent literature has looked at the role of financial incentives (Powell-Jackson et al., 2015; Gupta, 2021), co-working (Chan, 2016), peer pressure (Silver, 2021), and scheduling (Chan, 2018).

More specifically, this paper complements the recent literature studying the workload-quality trade-off in the healthcare sector.[2] Mixed evidence has been found on how workload affects physicians' decisions. Shurtz et al. (2022) evaluates how physicians' decisions depend on their daily workload and finds that physicians provide higher diagnostic inputs and lower drug prescriptions on high-workload days. Neprash (2016) finds that when physicians fall behind schedule, they spend less time with their subsequent visits, order fewer procedures, and provide fewer diagnoses. Freedman et al. (2021) investigates how primary care providers react to moments of high time pressure induced by cancellations and add-ins, finding such pressure pushes physicians to provide fewer diagnostic inputs, more follow-up care, and lower referral rates. The main contribution of this paper, relative to existing studies, is to causally examine how physicians' direct response to longer reviewing time, as opposed to indirect measures of workload or time pressure, affect the quality of their care and the treatments provided.

Second, this work relates to the literature on the impact of time pressure on output quality, which harks back to Tversky and Kahneman (1974). Some recent experiments have provided compelling evidence in favor of the argument that greater time pressure increases risk-taking behaviors (Kirchler et al., 2017; Essl and Jaussi, 2017; El Haji et al., 2019), and

[2] This issue has also been studied in the service industry (Tan and Netessine, 2014; Bruggen, 2015), banking industry (Xu et al., 2022), and justice system (Coviello et al., 2015), among others.

leads to more misjudgements (Suri and Monroe, 2003; Cao et al., 2022), especially among female participants (De Paola and Gioia, 2016). Frakes and Wasserman (2017, 2020) estimate the causal relationship between the time allocated to review patents and the examiners' effort, showing that lower examination time leads to reductions in examination scrutiny and to granting patents of weaker-than-average quality. This paper contributes to this literature by causally estimating the relationship between reviewing time and physicians' performance in a setting in which these workers operate as single units in a single-stage process. Furthermore, this paper looks at the incentives at play, highlighting that seniority-based contracts might lead to inefficient time-to-input utilization.

The remainder of the paper is organized as follows: Section 2 explains the institutional setting. In Section 3, I present and describe the data used. Section 4 exposes the empirical strategy followed. Section 5 presents the main results, and Section 6 provides a quantification exercise. Finally, Section 7 concludes.

2 Institutional Setting

2.1 Spanish Healthcare System

In Spain, healthcare is universal and free of charge. Its provision is structured around two main actors, Primary Care Centers and Specialized Care Centers, which together form Basic Health Zones (hereafter, BHZ). A BHZ is an administrative unit containing several Primary Care Centers mapped into a Specialized Care Center. Individuals are sorted into different BHZs based on their place of residence. Specialized Care Centers cover multiple services, such as the intensive care unit, the emergency room, and the outpatient department, which are usually located in hospitals.

This study focuses on the outpatient department. Initial access to this department is solely decided by the patients' treating primary care center, which allocates them to outpatient physicians based on their availability upon analyzing the patients' health conditions. The referral notification from the primary care center to the outpatient department is provided to patients some days after a patient visits her general practitioner, including information on the appointment time and date and the physician's name. This implies that the individuals' place of residence fully determines their outpatient department of reference, disallowing walk-in visits and blocking patients from choosing among clinics. Moreover, the region in which the department of my sample operates, Catalonia, does not allow patients to choose their outpatient physician, minimizing any possible relationship between physicians and their patients before a first visit.

2.2 Hospital Management Flow

The hospital manages patients following a production-line approach. Upon arrival, patients register at the main counter, where the administration secretary gives them directions to their waiting room and electronically notifies the physician in charge of the patient's arrival. From the waiting room, the physician calls patients following the appointment schedule, keeping track of who is in the waiting room. After the visit is completed, if a follow-up visit is ordered, patients return to the main counter, selecting the date and time slot of the follow-up visit within the physician's date recommendations. Throughout this process, physicians have full access to real-time information on all patients' availability status and health conditions.

Figure 1 presents the type of agenda displayed to physicians. At any given time, a physician knows precisely those patients who have not yet shown up, those who have canceled their visits, and those who are already in the waiting room. Physicians are also presented with patient characteristics, such as the patient's name and residence. In our example, a given physician is looking at her schedule at 10:00 a.m. The physician has already seen six patients, while one did not attend their 9:00 a.m. appointment. She has four more visits until the end of the shift, one of which was already canceled. Moreover, the physician is working ahead of time, as she has already completed the appointment scheduled to start at 10.00 a.m. Due to such a comprehensive information system, physicians have a complete picture of their shift, allowing them to react on the spot to changes such as cancellations.

Over the course of a shift, physicians are mandated to provide care to any patient with an appointment and update their patients' medical records. When physicians experience a cancellation or finish a visit faster than expected, they use that extra time to catch up on their schedule and fulfill their updating obligations. Additionally, physicians are provided with non-scheduled time for coffee and lunch breaks. Furthermore, following their pre-booked appointment order, physicians must finish all their visits on their corresponding appointment date.

3 Data

3.1 Hospital Data

I use data from one Spanish medium-sized, contracted hospital covering a wide range of specializations in the metropolitan area of Barcelona. My dataset contains all the 67,530 first visits to outpatient physicians from January 1, 2016, through June 30, 2018, assigned to 86 physicians covering 19 different specializations. These physicians always operate within their specialization, giving clear-cut advice to patients referred from Primary Care Centers. Physicians are also involved in other minor tasks not included in the present study, such as night shifts, surgery visits, and rehabilitations.

This dataset consists of high-frequency visit times and medical treatment information. It includes information on the patient's time of arrival in the hospital, the visit appointment time, the referral date, and the visit starting and ending times. Visit length is measured according to the time that the patient's profile was opened and closed on the physician's terminal. These times are automatically recorded by the terminals used rather than being self-reported by physicians. Referral and appointment dates are also crucial for reconstructing the entire outpatient process, from the first visit to all subsequent follow-up visits. Outpatient processes are used to test whether and how longer first visits affect the overall outpatient process. The dataset also covers the treatments provided in each visit, such as imaging and laboratory tests, drugs prescribed, and the testing cost.[3]

Table 1 provides descriptive statistics for the variables used in the analysis. For instance, the average patient is a middle-aged Spanish woman living in an area adjacent to the hospital and with public coverage. The average first visit takes 12 minutes, with an average waiting list of 30 days and an 8% likelihood of receiving a diagnosis.[4]

3.2 Shift Distortions - Cancellations

A standard work shift is from 9 a.m. to 1.30 p.m., with a structure and composition decided ex-ante on a yearly basis, being specific to the physician's specialization. Shifts are char-

[3] We cannot retrieve the drug costs as prescriptions are issued based on the drugs' active components. See Law 29/2006.

[4] The hospital managing our outpatient department is considered a high-performing center within the Catalan health system. To give a few examples, as of 2017, i) the reported patient satisfaction was 8.2 out of 10 in my outpatient department (7.5 in the region); ii) the probability of readmission within 30 days was 9.22% (9.81% in the region); and iii) the average waiting time to access a first visit was 41 days (121 days in the region). For those reasons, I consider the results presented in this study as a lower bound when compared to other outpatient departments.

acterized by being fully booked (the average waiting time for a first visit is 30 days) and compulsory for the physician (i.e., the physician cannot prioritize or decline visits). The whole dataset available contains 347,277 scheduled visits, divided into first visits (24.43%), follow-up visits (50.10%), and external consultations (23.06%). Figure 2a shows how the encounters spread over the shift by visit type. The period from 9 a.m. to 1.30 p.m. is the busiest, with 86.54% of the visits being concentrated in that period. While the outpatient department uses the hospital facilities in the morning, they are used later in the day for rehabilitations and surgeries, which are not included in the study. First visits spread homogeneously along the shift.

Cancellations represent the main perturbations on the physicians' schedules, providing unexpected free time. I use only those that occur on the visit date, as those happening on a prior date are easily re-booked. In absolute terms, the whole dataset contains 54,057 on-the-day cancellations, comprising visits withdrawn before their appointed slot (18%) and no-shows for a visit (82%). No patient walk-outs are found in the data. Figure 2b shows the share of cancellations over the shift using all the visits' appointment times at the 30-minute bin level. Visually, there is no clear pattern indicating clustered cancellation periods.

I focus on how prior cancellations affect subsequent first visits during a shift. Using the benchmark sample as in Table 1, Figure 2c shows that the number of cancellations before a given visit accumulates over the schedule, with higher variation in the evening shift due to the combination of newly arrived physicians with those who are continuing from the preceding morning shift. Figure 2d shows the evolution of the probability of having the previous visit canceled, exhibiting a higher incidence at the beginning of the morning and evening shifts. Hour fixed effects are used in the study to account for such variation in the propensity of receiving a shock.

Figure 3 exposes the distribution of first visits with respect to prior cancellations. Subfigure 3a presents the fraction of visits with no prior cancellation and the fraction with a prior cancellation at higher horizons. In total, 62% of all the first visits had at least one preceding visit canceled, and 16% had the prior visit dropped. Subfigure 3b presents how the average actual and expected visit lengths evolve with respect to the distance from a prior cancellation.[5] We can appreciate that i) the hospital structurally assigns more time-consuming visits to earlier slots, where there is a lower probability of having any prior cancellation; ii) when shocked with a cancellation, physicians spend more time on their next visit; and iii) for all distances, expected visit length is generally greater than the actual visit length, which

[5] Expected visit length is a measure provided by the outpatient department, which identifies how much time an average visit should take, based on the type of visit, specialization, and administrative duties involved.

shows that the outpatient department provides visits with insufficient time to compensate for overbooking and other administrative duties.

Lastly, Figure 4 makes transparent the heterogeneity of performance, in terms of visit length, observed for physicians working in diverse specializations. We can observe that physicians' visit length widely varies between 7 and 26 minutes per visit, and by construction, it negatively correlates with the number of cancellations per day. However, the average time spent by physicians reviewing patients does not predict whether their visits will be affected by prior cancellations nor whether physicians will have higher testing, prescribing, and diagnosing probability. Physician fixed effects are used in the study to account for such variation in average visit lengths.

4 Empirical Strategy

In the first empirical exercise, I examine the extent to which medical treatments are influenced by the time spent on a visit using the following model:

$$Y_{i,j,s} = \beta_0 + \beta_1 Length_{i,j,s} + \theta T_s + \delta_j + \Psi X_{i,s} + \varepsilon_{i,j,s} \quad (1)$$

where Y identifies a given visit outcome, as described in Section 4.1, for a patient i, a physician j, and a slot s. The key independent variable, *Length*, identifies how many minutes a physician j spends with patient i in a visit slot s. I control for patient characteristics, $X_{i,s}$, such as gender, age, nationality, insurance coverage, and district distance to the hospital. All regressions include i) physician fixed effects, δ_j, which allows us to account for time-invariant variation across physicians, and by construction, across specializations; ii) month-year fixed effects, T_s, which mitigate the fact that results are confounded by seasonality (e.g., periods in which patients are more prone to suffer from diseases, such as with the seasonal flu, may also lead them to miss their hospital visits more frequently); and iii) hour fixed effects, T_s, which accounts for different hour-patient compositions.

Estimating Equation 1 using OLS may result in biased estimates for several reasons. First, there could be omitted variables not captured by the rich set of controls and fixed effects. These confounding variables may correlate with our measure of visit length and with some unobserved components in the error term. For example, physicians' good/bad moods or health conditions may affect both visit lengths and medical treatments. Second, given that physicians have complete information on all their on-the-day visits, they may allocate visit lengths based on their current and future patients' characteristics. Such anticipation may facilitate simultaneous causation between the time spent with patients and the treatment provided. On the one hand, physicians may decide to spend more time with those patients found to be more challenging, allowing them to assess better if further treatment is required. On the other hand, physicians may decide to provide patients with treatments as a substitute for the time spent. Such substitution decision is plausible as reviewing and testing physicians may differ. To tackle these concerns, I only use first visits, as patients accessing these initial visits have no knowledge of the physician's schedule, nor do physicians know these patients; and use cancellations as an exogenous variation on the physicians' disposable time.

I use prior cancellations to capture exogenous variations in physicians' available time. Those cancellations comprise all the on-the-day visit withdraws, including those prior to their appointment and the no-shows. I define a first visit to be affected by a cancellation if the visit preceding it was canceled using its real cancellation time. In practice, $PriorCancel$ is a dummy variable that takes value 1 if the previously scheduled visit was a no-show,[6] or if another visit, which is supposed to happen later in the same day, is canceled during the current visit. Using the exact cancellation time is important for the study, as physicians can smooth out cancellations for which they have been notified. I use this approach since it represents a lower bound of the impact a cancellation has on subsequent visits, taking as not treated any other first visit that is not immediately after a cancellation. Figure 5a displays how cancellations impact the length of subsequent visits. We can see that physicians utilize significantly more time in visits after a cancellation than before. The figure also highlights that the time used in those first visits right after a cancellation is significantly larger than any other first visit. Figure 5b shows that physicians cannot anticipate cancellations, changing their reviewing time accordingly. For these reasons, the present analysis defines a treated visit as a first visit immediately after a cancellation, and all other first visits as not treated.[7]

The validity of the instrument hinges on various considerations. The first issue relates to the random assignment of cancellations. Those patients dropping a visit do so without knowing the physician's schedule. However, visits could be still more frequently canceled when certain patient characteristics, such as older patients or those with more chronic problems, are present. Moreover, physicians could also decide which patients to take, after a visit gets canceled. Table 2 displays the covariate test on the patient characteristics and the shared physician-patient characteristics. Prior cancellation does not predict any patient char-

[6] A no-show is a visit for which its patient never showed up. In other words, I do not leverage on the *extra* visiting time provided by those *pending* patients who did not show up on time to their visits but showed up later in the shift.

[7] Table A1 shows that prior cancellations lead to extra visiting time for all patients reviewed during the physician's shift. Prior cancellations do not lead to extra reviewing time when physicians work overtime.

acteristics used in the study, which are visible to physicians. More importantly, physicians do not select patients based on their shared characteristics, namely sex and age. This fact supports the claim that first visits are randomly affected by prior cancellations.[8]

A second issue pertains to any other utilization of the physician's extra disposable time created by a prior cancellation. Prior to the treated visit, physicians decide how fast to take the new patient, which, in turn, might reduce their working delay. In turn, the estimates presented would be biased if such a less-rushed environment directly affects medical treatment, not only via visit length, thus violating the exclusion restriction. This indirect path is mostly attenuated by the use of fixed effects at the hour and the physician level, as the visits with a prior cancellation are compared to adjacent visits with similar levels of time pressure. Nevertheless, it could still be the case that the allocation of such extra time affects the first visit after a cancellation significantly differently compared to those at different horizons. To test whether a less-rushed environment directly affects the outcomes of interest, I extend Equation 1 to include the variable *Delay*, which represents the difference between the visit start time and the visit appointment time. The average *Delay* in the sample is 16.2 minutes. Following Neprash (2016), I instrument the variable *Delay* using a dummy variable which indicates whether the preceding realized visit arrived late to her appointment time, $PriorLate$. The variable takes value 1 if the patient appointed before a given visit arrived at the outpatient department after her scheduled appointment. When patients arrive late to the outpatient department, physicians await them for some courtesy time, which might lead to higher delays suffered by the following patients.[9] Table A4 evidences no clear link of *Delay* directly affecting visit outcomes. Moreover, when comparing the variable *Length* in Table A4 to the main result provided in Table 3, we can see how including *Delay* does not affect the predictability of our variable of interest. For such reasons, I dismiss the premise that, in the context of this study, changes in time pressure, originating from sudden schedule changes, affect the outcomes of interest other than through the visit duration.

4.1 Outcomes of Interest

I use the previously detailed instrumental variable framework to study how physicians respond to extra time, examining a broad set of outcomes that can be classified into diagnosis

[8] As an exception, some specializations in the outpatient department allow their first-visit patients to choose their preferred slot at their corresponding Primary Care Centers. Using only those patients, Table A2 shows that having a prior cancellation is not predictive of either those patients' characteristics or the shared physician-patient characteristics.

[9] Table A3 tests whether the instruments $PriorCancel$ and $PriorLate$ predict observable patient characteristics, finding no systematic evidence.

provision and treatment choice.

Regarding diagnosis provision, I investigate whether longer visits are beneficial in assessing patients' diagnoses. Given that the outpatient department's main objective is to provide a correct assessment of the patient's problems due to their clear-cut medical knowledge, I use the provision of a diagnosis, *Diagnosis*, as a proxy of a visit's successful completion. According to Aranaz et al. (2005), the probability of a diagnostic error in the Spanish healthcare system is 0.13%. It is important to note that making a diagnosis is not excludable from providing other inputs, such as testing, as physicians use tests to assess and corroborate diagnoses. Following that logic, I include as an outcome a variable identifying whether the current first visit had a follow-up visit in the same hospital, named *Follow-up*.

Referring to the treatment choice, I investigate whether visit length is used as a substitute or complement to the provision of tests and drugs during the visit. On the one hand, physicians with extra visiting time may examine patients more thoroughly, inspecting their symptoms more carefully, reducing the need for intensive testing. In such a case, testing would be a substitute for visit length. On the other hand, visit length could complement intensive care as physicians with such extra visiting time could further deepen their knowledge of the clinical case and consequently order more tests. Moreover, extra visit length would give physicians a clearer idea of the patient's needs, thus modifying their drug prescription to more accurate doses.

The variables used to explore how visit length relates to treatment choices are i) *Tests*, which is a dummy variable measuring whether medical tests, e.g., imaging and laboratory tests, have been ordered, ii) *Num. Tests*, which is a variable identifying the absolute number of tests ordered in a given visit, iii) *Test Cost*, which measures the total cost of the tests ordered, iv) *Drugs*, which is a dummy variable measuring whether drugs have been prescribed, and v) *Num. Drugs*, which measures the total number of drug doses ordered in a given visit. I compute the testing cost using internal cost information provided by the outpatient department in the sample. As for the number of drugs prescribed, I follow the aggregation method based on the Defined Daily Doses prescribed as proposed by the WHO. A Defined Daily Dose is a measure of drug utilization that stands for the assumed average maintenance dose per day for a drug used for its main indication in adults. I use this measure instead of the number of drugs provided, as it aggregates different drug groups weighted by their relative intensity, avoiding issues related to the drugs' package size and strength.

5 Results

Table 3 reports the estimation results using the 2SLS model previously outlined.[10] Column 1 introduces our first stage estimates using *Prior Cancel* as the source of exogenous variation and controls by a comprehensive set of fixed effects. Our first coefficient of interest, *Prior Cancel*, tells us that when shocked by a cancellation, physicians spend an average of 1.62 minutes more with the following patient than with any other patient with no immediately prior cancellation. Such a significant effect represents an increase of 12.8% over the average visit duration. It corresponds to the lower bound effect of a cancellation's impact on visit duration, given that visits at higher distances from a notification, used in this study as controls, may also be affected.

In Column 2, I test whether longer visit duration helps physicians to assess patients' diagnoses. We observe that longer visits positively affect the provision of a diagnosis, implying that for every minute spent with a patient, the probability of providing a diagnosis increases linearly by 0.36 percentage points. In other words, compared to the average probability of providing a diagnosis, every extra minute spent with a patient translates into a 4.39% higher chance of providing it. However, the positive relationship between visit length and diagnosis provision could be both measuring a more in-depth examination process driven by longer reviewing time and the fact that physicians had enough time to record the diagnosis. I test that hypothesis by identifying the most repeated diagnosis for each specialization. On the one hand, it could be that the extra time physicians use would only lead to a higher finding rate because they have the time to record the diagnoses or because they are more prone to fall to patients' diagnostic demands. In such a case, both common and uncommon diagnoses would be recorded more frequently as the visit length increases. On the other hand, physicians may use the extra visiting time to provide a more in-depth examination, providing significantly more uncommon diagnoses, since they can screen patients more thoroughly, thus providing more accurate diagnoses. Table 4 shows longer reviewing time leads to more uncommon diagnoses, while no effect is found on the provision of those diagnoses repeated most frequently. In fact, providing a common diagnosis takes 12.5 minutes, while an uncommon diagnosis requires an average of 13.3 minutes, suggesting that physicians use extra reviewing time to provide a more precise service.

Back to Table 3, we investigate how visit length affects input choices. In Column 3,

[10] For completeness, I include in the Appendix the benchmark specification without controls (Table A5), the ITT estimation (Table A6), and the OLS estimation (Table A7). They are quantitative and qualitatively similar to the benchmark estimation. Similarly, Table A8 in the Appendix replicates the benchmark specification using as instrument the number of cancellations that happened before a given visit.

I explore how reviewing time causally relates to the probability of ordering tests during a given visit. The variable *Length* shows that for every extra minute spent reviewing patients, there is an increase in the probability of ordering a test by 0.65 percentage points. Compared to the average visit ordering pattern, a one-minute increase in the visit length due to a prior cancellation implies a 3.6% higher chance of ordering tests. Column 4 broadens the outcome definition by checking whether visit duration affects the number of tests ordered. As in Column 3, we can see how increased visit duration leads to more tests. The estimated effect is low in magnitude, with an increase in the number of tests of 0.0096 per extra minute spent on the consultation. Despite that, compared to the average number of tests ordered, we can see how an increase of one minute in the visit duration implies a 3.35% increase in the number of tests ordered. These two results suggest that test ordering is used to complement visit duration, meaning that when physicians are exogenously exposed to more time, they employ it in ordering more tests. Due to the right-skewed test-ordering distribution, as shown in Table 1, the main driver in this relationship is the extensive margin. Column 5 further checks whether increases in visit duration affect testing costs. We can see how a unit increase in visit duration corresponds to an increase in *Test Cost* of €0.8. That means an extra minute on a consultation translates into a 6.35% increase in the average testing cost. This implies that visit duration and total testing cost are complementary inputs.

In Columns 6 and 7, I focus on drug prescription. Column 6 shows that visit duration does not affect the probability of prescribing drugs. However, it does have an effect on the dose prescribed. Column 7 shows how an increase of one minute in a given visit weakly reduces prescription doses by 0.4 units. That sizable effect represents a 20.1% reduction in the average dose. These results indicate that providing time to physicians helps reduce the overall dose provided to patients, acting as a substitute for reviewing time. Under the assumption that a longer visit duration helps the physician to have a clearer idea of the patient's problems, the provision of lower doses of drugs could be understood as a convergence to the optimal prescription.[11]

Lastly, Column 8 analyzes whether a longer visit duration affects the probability of having a follow-up visit. On the one hand, physicians might decide to provide patients with a follow-up visit at the hospital because a more extended visit might imply further tests to be checked in situ. On the other hand, the extra visit length might help assess the patient's diagnosis better, thus redirecting the patient back to the primary health care center of origin. We

[11] The medical literature has found negative correlations between consultation length and medical over-prescription, suggesting that longer visits help physicians investing time on the patients' education and psychological support (Dugdale et al., 1999; Ventelou et al., 2010; Allen et al., 2022; Neprash et al., 2023).

can observe how a one-minute increase in visit length increases the probability of a follow-up visit by 0.92 percentage points, representing a 3.28% increase over its mean. Table A9 shows that a one-minute increase in reviewing a first visit leads to an increment in the total clinical case duration of 1.16 days. This result suggests that physicians' complementary use of time and testing, during first visits, leads to slightly longer clinical processes.

All these results suggest that visit length is a key factor in understanding input utilization. However, they could hide an intertemporal input substitution decision followed by physicians, motivated by the extra time available during their first visits. If this were the case, we would expect physicians who were *shocked* during a given first visit to inversely adjust their input utilization during the corresponding follow-up visit.[12] Table 5 tests such a hypothesis, using a similar strategy as in Table 3, in a subsample of first visits with a follow-up visit in our outpatient department. We can see how increases in visit length during the first visit do not significantly impact the input utilization during the follow-up visit. This result reinforces the idea that physicians do not use extra visit length to transfer treatments intertemporally; instead, they provide patients with extra care they would not have otherwise received in their medical process.

Column 7 in Table 5 introduces a new variable identifying whether the same physician conducted first and follow-up visits. We can see how increasing visit length during a first visit affects the probability of having the same treating physician in an eventual follow-up visit. For every extra minute spent on a first visit, the likelihood that a patient will continue with the same physician increases by 1.05 percentage points. On the one hand, this result could be driven by physicians who, having a more exhaustive knowledge of the patient's case, might decide to keep their patients during their follow-up visit. On the other hand, this result could be driven by patients who, having a higher satisfaction from their longer first visits, might avoid cancelling their follow-up visits with their treating physician. Table 6 provides further evidence that physicians are pushing for preserving their patients and not the other way around. Physicians achieve this by securing that ordered diagnostic procedures are ready when a follow-up visit occurs, thus keeping the same patients over time. In practice, for every extra reviewing minute spent in a first visit, the probability that physicians cancel the follow-up visit decreases by 12.9%. No effect is found on patient-motivated cancellations.

These results suggest that physicians use the extra time to assess the patient diagno-

[12] I test whether having a prior cancellation predicts any patient characteristic in the sample of follow-up visits. Table A10 in the Appendix shows no systematic sample selection based on observable patient characteristics.

sis better, to recommend further intensive care treatments, and to correct drug prescription excess. Nevertheless, how intensely physicians use such time might depend on multiple factors. In the following subsections, I explore whether patients' characteristics are key in understanding time utilization and shed light on the relevance physicians' contracts have on such a relationship.

5.1 Which Patients' Characteristics are Driving These Effects?

In this section, I explore the influence patients and shared patient-physician characteristics have on time utilization.

I begin by examining whether the gender of patients influences how physicians use extra visiting time. While patients may differ in required treatments along their gender, the exogenous exposure to cancellations allows us to study whether physicians treat them differently. Table 7 shows that visit length affects male and female patients differently. Firstly, we can see that after the realization of a cancellation, physicians employ more time similarly with both male and female patients. Nevertheless, physicians use such extra time only input-intensively with female patients, with increased tests ordered and a lower prescription dose. This differential input use is not explained by a systematic difference in their unconditional means (i.e., 12.4 minutes for men, and 12.7 for women), suggesting some limited preferential treatment towards women. I further inspect whether physicians treat patients differently depending on whether they share the same gender as the patient. On the one hand, we could expect that physicians use time more intensively on those patients sharing their gender, following their probable higher *proximity*. On the other hand, given that physicians might be able to screen those patients sharing their gender more quickly, we could expect that extra visiting time could be only used efficiently on patients of other genders. Table 8 shows that, when exposed to cancellations, physicians use extra visiting time more intensively only with those patients with a different gender. Putting both results together, they suggest that physicians provide more intensive care to female patients and those patients who do not share their gender.

I then look at whether physicians treat patients differently based on their nationality. Following the previous approach, Table 9 analyzes whether physicians treat native patients differently than those born in other countries. While both national and non-national patients get more consultation time after a cancellation, physicians only provide diagnostic inputs and more tests to national patients. The patients' inherent characteristics do not explain such differential productivity by physicians. This differential input use is not explained by a systematic difference in their unconditional means (i.e., 12.6 minutes for national patients, and 12.5 for non-nationals). Moreover, the outpatient department considers non-national patients, if anything, more demanding, indicated by providing them longer expected visit lengths, 15.17 minutes, compared to 14.8 minutes for national patients. The results highlight that, although the outpatient department considers non-national patients more demanding, physicians provide a more valuable service only to national patients when given extra visit time.

Next, I focus on the treatment physicians provide to patients depending on how many days patients had to wait to access the outpatient department. As previously explained in Section 2.1, patients are scheduled for a first visit with an outpatient physician at their primary care health centers. At that level, given the hospital scheduling limitations, primary care physicians can decide to speed up patients' first visit with a specialist, implying that those patients with worse health conditions will be granted appointments at shorter notice and flagged as urgent to the outpatient physician. Moreover, given that accessing the emergency room is always an option, those patients waiting for an extended period will presumably be those with less urgent health issues. Table 10 provides evidence that physicians use extra visiting time differently depending on the patient's waiting time. Physicians use longer visits to order more tests, decrease the drug dose prescribed, and provide a diagnosis, but only for those patients whose waiting time was below the average time for their specialization. These results suggest that physicians internalize the time patients wait for the first visit, providing more urgent patients with a more valuable service.

Overall, the way physicians use extra visiting time greatly depends on the patient's inherent characteristics and the physicians' specialization. These results highlight that physicians' reaction to the relaxation of their time constraints is not monotonic across subgroups, especially favoring female, Spanish-born, and more urgent patients.

5.2 Role of Physicians' Contracts

In this section, I study how physicians' contracts shape how extra visiting time is used.

According to the general Spanish healthcare legislation, physician's contracts are composed of two main components: a fixed wage, common to all physicians; and a flexible component, which is mainly determined by the physician's tenure.[13] These contracts are updated annually on a per-physician basis, including adapting visit workloads according to

[13] The fixed component is similar across physicians as it is based on educational attainment, which is, by law, required to be a bachelor's degree in medicine and to have passed a national exam (See Art. 4 in the Royal Decree 127/1984).

the physicians' responsibilities and tenure, which might ultimately lead to a differential use of the extra time provided by cancellations.[14]

I use physicians' age as a proxy of their tenure, given that i) physicians enter the medical market right after finishing their studies,[15] and ii) the market for physicians enjoys low unemployment.[16] I define physicians to be senior if their age is higher than the median age ($\approx$ 50 years old); otherwise, I define them as junior. As indicated previously, the older physicians are, the more seniority they are likely to have, thus the higher their salary. While the hospital has the incentive to retain these experienced physicians, it cannot freely raise the physicians' salaries, which are publicly regulated. Therefore, senior physicians have to be compensated with more advantageous shifts instead. Table 12 shows that senior physicians' schedules include lower numbers of patients per hour and fewer overbooked visits, while the expected visit duration is similar to that of junior physicians. Furthermore, Table 13 shows that patients visiting senior outpatient physicians do not differ systematically from those visiting their junior colleagues. These tests show that while seniority affects the physician's workload through more relaxed schedules, it does not imply a change in patient composition.[17]

Back to our benchmark specification, Table 14 shows that extra visit duration affects the input utilization differently, depending on whether that bonus time is provided to senior or junior physicians. The first insight we obtain from Columns 1 and 2 is that both senior and junior physicians similarly react to cancellations by increasing the reviewing time with their subsequent patients. Despite such similar increase in visit length after a cancellation, the unconditional visit length for junior physicians is 11.7 minutes, while for their senior colleagues, 14 minutes. This shows that even if junior physicians were to utilize more time, it would not be enough to compensate for the difference between the average visit length between these two groups. The way contracts are formulated, being physician-specific, facilitates less rushed environments for older professionals at the expense of their younger colleagues.

This formulation fully determines how extra visit length is used. In Column 3, we can

[14] For further knowledge on the collective bargaining agreement, please refer to the Resolution EMO/1742/2015 present in the Catalan Regional Bulletin n. 6923.

[15] According to the Spanish Health Ministry, the average age of those physicians entering practice in one of the specialties covered in the sample is 26 years, which corresponds to the age at which students finish their studies (Spanish Health Ministry, 2015).

[16] According to the Spanish Health Ministry, physician's unemployment in 2017 was 2.32% (Spanish Health Ministry, 2019). The unemployment rate in Spain in 2017 was 17.22%.

[17] A total of 13.67% of the visits correspond to 16 physicians who did not want their data to be made public. This section does not consider them.

observe that junior physicians use extra visiting time more effectively by providing more diagnoses. Every extra minute a junior physician spends with a patient increases their probability of providing a diagnosis by 0.73 percentage points, i.e., it increases the probability of providing a diagnosis by 9.56% compared to its average. On the opposite extreme, despite spending more time with patients affected by a prior cancellation, senior physicians do not use such *bonus* time to modify their diagnosis provision. These results suggest that visit length expansions are not output-efficient for physicians already enjoying more relaxed schedules. Table 15 shows how the extra visiting time helps only junior physicians to provide a more in-depth diagnosis, measured by more uncommon diagnoses. This result suggests that junior physicians effectively use the extra time to provide a more valuable service.

Back to Table 14, I display in Columns 4 to 8 how consultation time affects input choices. On the one hand, when exposed to extra time, junior physicians provide patients with more tests at intensive and extensive margins and leading to higher cost. Quantitatively, for every extra minute a junior physician spends with a patient, the probability of ordering a test increases by 0.68 percentage points (representing a 4% increase over the average ordering probability), the number of tests ordered is increased by 0.013 units (representing a 4.88% increase over their average ordering rate), and total testing cost increases by 10.8%. On the other hand, longer visits affect the drug dose level prescribed to patients, as in Table 3, through the intensive margin. For every extra minute a junior physician spends with a patient, they decrease the average dose prescribed by 0.68 daily defined doses (representing a reduction in the prescription dose level by 28.82% when compared to their average dose prescribed). Similarly, senior physicians decrease the patient's prescriptions by 0.19 doses (reflecting an average reduction of 8.24% in the prescription doses).[18]

These results highlight that correcting insufficient time per visit might have welfare-improving effects, as in the case of junior physicians. For senior physicians, longer visits do not entail further care expansions, suggesting they are already at their optimal level of time-to-input utilization. These results suggest that defining schedules based on seniority might hinder high costs related to suboptimal utilization of visiting time. In Section 6, I provide a quantification analysis stressing these inefficiencies and show that time expansions to less experienced physicians might be cost-effective.

[18] In the same spirit, Table A14 shows that extra visiting time helps least productive physicians catching up in the care provided, while no effects are found on high-performing doctors. Table A15 compares only physicians in the 1st and 4th quantile of the physician's age distribution, finding comparable results to the benchmark specification.

6 Quantifying the Cost of a Diagnosis

In this section, I quantify the direct cost of increasing visit lengths.[19] Suppose we want to increase the probability of providing a diagnosis by one percentage point ($\approx$ 12% at the sample average). We can achieve this in two ways: i) by increasing all physicians' visiting times; or ii) by favoring only those physicians with less experience.

6.1 Broad Increase

Let us say we opt to increase the length of all first visits to achieve a one-percentage-point increase in the diagnosis rate. That can be achieved with an increase in the average visit length of 2.77 minutes, using the IV-fixed-effects estimates in Column 3 of Table 3.

We calculate the direct costs associated with increasing visit length such that it increases the diagnosis rate by one percentage point, assuming that physicians will optimally utilize their *bonus* visiting time. In our case, using a linear approximation, we have the following:

$$\hat{\Delta}_{minutes} = 2.77 \times 6.55 \times 102.44 \ = 1,858.62 \text{ minutes per year and physician}$$

where 6.55 refers to the average number of first-visit patients per day and physician, and 102.4 is the average number of days worked per physician. $\hat{\Delta}_{minutes}$ amounts to about 31 hours extra per year and physician, representing a 1.8% increase in the physician's yearly working hours. We now extrapolate our physician-specific estimates to the general Spanish economy, such that:

$$\hat{\Delta}_{cost} = \hat{\Delta}_{minutes} \times (0.5876 \times (1 + 0.0092 \times 10.55) + 0.8045) \times 76,562 \ \approx € 206m$$

where 0.5876 represents the average physician wage per minute,[20] 0.0092 represents the increased probability of scheduling a follow-up visit due to a one-minute increase in the first visit duration, and 10.55 the average follow-up visit length. 0.8045 represents the average

[19] Throughout the exercise, I assume that the outpatient department's fixed capacities are non-binding along small visit length expansions. Similarly, I do not internalize the positive crowding-out effect more prolonged first visits have on other services, such as the emergency room.

[20] The average working hours of a physician in the Spanish health system is 1,645 hours, regulated by Decree 2/2012 and Royal Decree 20/2012. The average outpatient physician salary in 2018 is €58,000 (Medscape, 2019).

treatment cost ordered for every extra minute spent with a patient,[21], and 76,562 refers to the total number of outpatient physicians in Spain in 2018 (Spanish Health Ministry, 2019). Thus, increasing the diagnosis rate in first visits by one percentage point would have an estimated labor cost of €206m for the general Spanish economy.

6.2 Tailored Increase

Suppose we now opt to provide more time per visit only to those physicians who will use it more efficiently. Following the previous procedure, I study how many more minutes junior physicians should have to increase their diagnosis rate by one percentage point. That can be achieved by increasing the visit length of junior physicians by 1.37 minutes, using the IV-fixed-effects estimates in Column 3 of Table 14. This change at the visiting intensive margin helps junior physicians assess their patients adequately while leaving senior physicians' schedules unchanged. Following the same structure as before, we have:

$$\hat{\Delta}_{minutes,junior} = 1.37 \times 6.82 \times 95.45 \;\; = 891.82 \text{ minutes per year and junior physician}$$

Now we extrapolate these changes to the overall economy, such that:

$$\hat{\Delta}_{cost} = \hat{\Delta}_{minutes,junior} \times (0.575 \times (1 + 0.0116 \times 10.09) + 1.294) \times 42,863 \;\; \approx €74m$$

where 0.575 represents the per-minute wage,[22] 0.0116 represents the increased probability of scheduling a follow-up visit due to a one-minute increase in the first visit duration, and 10.09 is the average follow-up visit length. 1.294 represents the average treatment cost ordered for every extra minute spent with a patient, and 42,863 represents the estimated number of junior physicians.[23]

In sum, comparing this targeted increase to the previous broad increase in reviewing time, it is more cost-effective in achieving the same result, a one-percentage-point increase in the diagnostic provision. With all due caveats, this exercise highlights how solely exploiting the contracting incentives based on seniority would allow for more efficient diagnostic

[21] The average treatment cost is calculated using internal information of the sample outpatient department. Both in this and the following calculations, it is assumed to be representative of the health system as a whole.

[22] The salary for junior physicians corresponds to a physician with a fixed position, around 40 years old, and 15 years of experience. The annual salary of such a physician is €56,755. For further reference, see OMC (2019).

[23] I use information from the OECD database - Healthcare Utilization. Given that the number of outpatient physicians is not tabulated by age, I assume that the distribution of physicians by age is the same for the overall population of physicians and that of outpatient physicians.

provision at a reduced cost.

7 Conclusion

This paper estimates and provides evidence of the inefficient time allocation in the Spanish outpatient system. I leverage its unique setting and cancellations as random time shocks to provide a causal interpretation of how the amount of reviewing time shapes physicians' decisions. Conceptually, I compare those first visits affected by an unexpectedly longer visit time caused by a prior cancellation to all other first visits, holding all other parameters in the environment constant.

I find that longer first visits lead to a higher likelihood of providing a diagnosis, the main objective of outpatient departments. The effect is driven by uncommon diagnoses, whose provision requires a more in-depth analysis, while no effect is found for the most common diagnoses. Longer first visits increase diagnostic input utilization while decreasing drug dose prescriptions. These results suggest that physicians use the extra visiting time to assess the patient's health problems in more detail and, in the event of indecision, to request further diagnostic inputs, ultimately improving the service provided. Moreover, I find no evidence of an input substitution effect between first and follow-up visits, suggesting that longer first visits have a lasting impact on the clinical process.

I then look at how relevant working contracts are in shaping physicians' decisions. While outpatient departments have the incentive to retain more experienced physicians, they might not be able to freely raise their physicians' salaries, as they might be publicly regulated, resorting to compensating them with more advantageous shifts instead. I find that junior physicians, whose contracts lead to more pressured schedules than their senior colleagues, use extra visiting time efficiently, while senior physicians do not. This result highlights, and I show quantitatively, that policies increasing all reviewing time across the board might prove inefficient.

This avenue of research is extremely important for policymaking, as it emphasizes that current promotion incentives might lead to inefficient input utilization. While this paper has focused on one Spanish outpatient department, the message of this study, concerning the effect of remedying insufficient reviewing time on the workers' decisions is more general. In fact, it relates to all those time-constrained situations in which workers must decide between speeding up their processes and exerting higher effort per task. This study indicates that public welfare may be improved by policies providing additional time to workers most in need.

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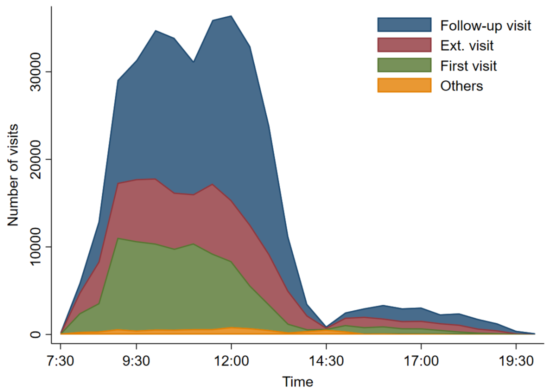
Figures and Tables

Figure 1: Daily Physician's Schedule Viewed at 10:00 am.

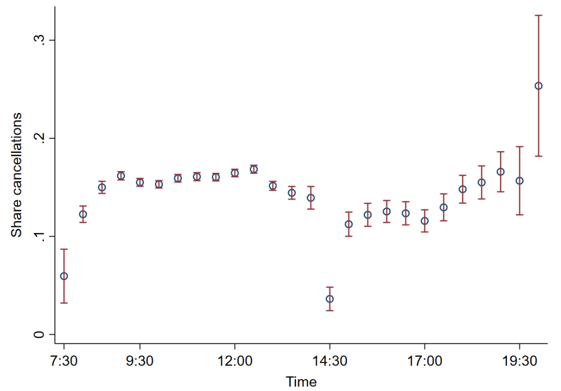
Appointment Time	Patient ID	Patient	Basic Health Zone	Status	Arrival time	Visit type
8:30	1	Antonio García Gracia	Barcelona 2-B	Completed	8:25	Follow-up
9:00	2	Jordi Bosch Fernández	Barcelona 3-A	Not present	-	Follow-up
9:10	3	Montserrat Muñoz Sánchez	Barcelona 4-D	Completed	9:05	First Visit
9:15	4	María del Carmen González Serra	Barcelona 5-D	Completed	9:00	First Visit
9:30	5	Anna Solé Pérez	Barcelona 1-C	Completed	9:10	Follow-up
9:40	6	José Giménez Sánchez	Barcelona 2-E	Completed	9:00	Long Cure
10:00	7	Wei Wang	Barcelona 8-B	Completed	9:40	Injection
10:15	8	María José Pérez Iglesias	Barcelona 4-C	Pending	9:45	First Visit
10:25	9	Montserrat Batlle Figueres	Barcelona 5-C	Pending	-	Follow-up
10:43	10	María del Mar Cardel Pérez	Barcelona 3-E	Canceled	-	First Visit
11:00	11	Mohammed Alaoui	Barcelona 5-A	Pending	-	Follow-up

Notes: The figure shows how the schedules used in the outpatient department look like, using fictitious information. *Appointment Time* refers to the time at which a patient is appointed to start her visit. *Status* refers to the visiting status, which can be "Completed" if the visit finished already, "Not Present" if the visit was supposed to happen but the patient was not present, "Pending" if the visit will happen later, and "Canceled" if the visit was appointed for a later time but canceled earlier on the day. *Arrival time* refers to their arrival time to the outpatient department. If *arrival time* is not displayed (e.g. −), it means the patient has not registered yet at the outpatient department. *Visit type* highlights broadly the type of visit, which can be "First Visit", "Follow-up", "Long Cure", or "Injection".

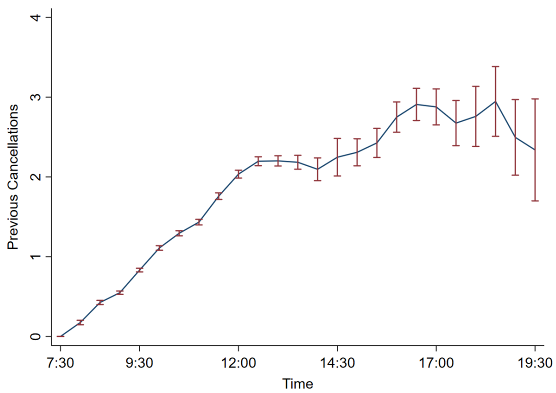
Figure 2: Distribution of Visits Over the Day



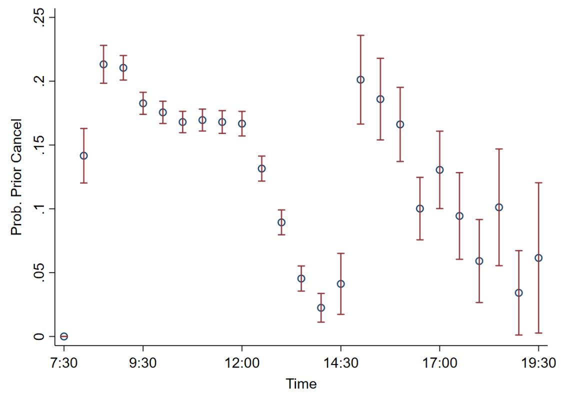
(a) Distribution by visit type



(b) Share of cancellations (Appointment)



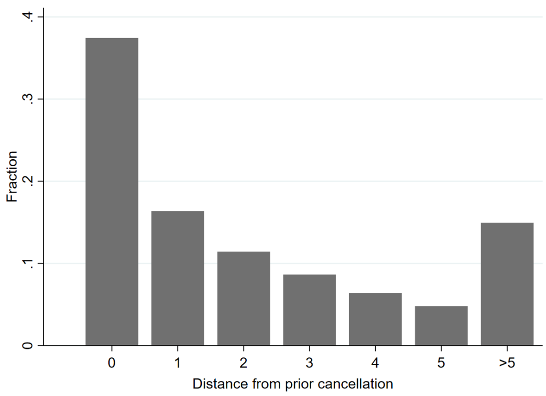
(c) Previous cancellations (First visits)



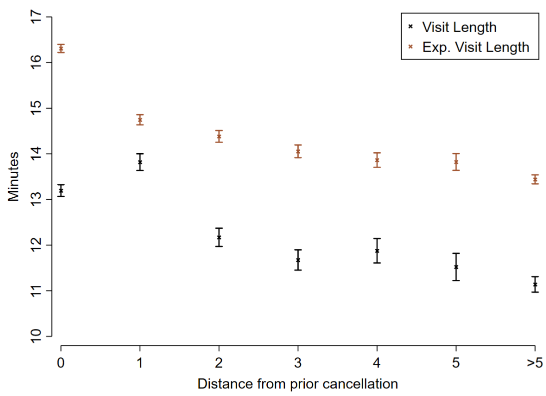
(d) Prob. Prior cancel (First visits)

Notes: The figure reports how visits and cancellations span over the schedule. Subfigures 2a and 2b use the sample including all the visits, namely first, external, and follow-up visits, canceled or not, while subfigures 2c and 2d only use our final sample of first visits. Subfigure 2b displays the share of cancellations as to when those visits were appointed. Subfigures 2c and 2d use the real notification time of those cancellations as in our main analysis. Prior cancel identifies those visits that had their prior visit slot canceled using their real cancellation time. All subfigures use 30-minutes bin sizes.

Figure 3: Distances to Prior Cancellation



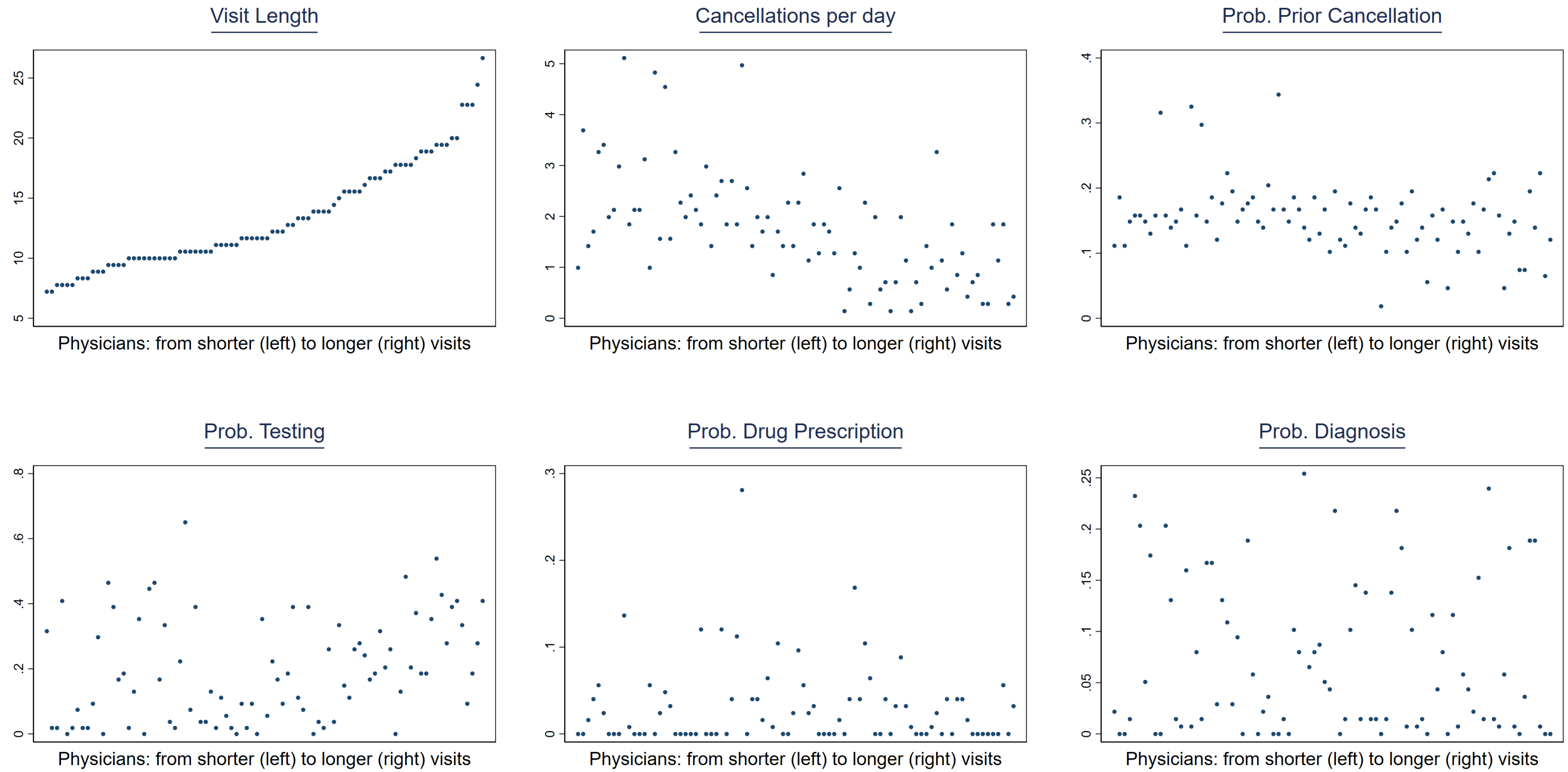
(a) Distribution



(b) Unconditional means

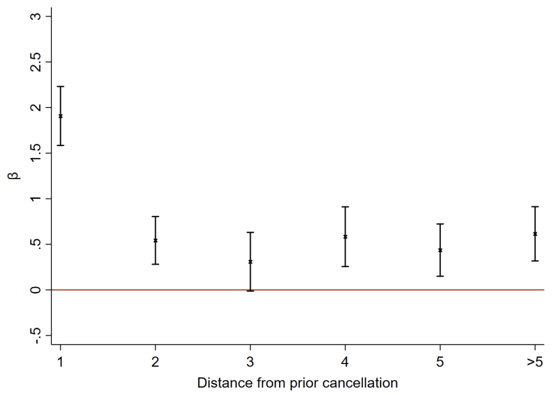
Notes: The figure reports the proportion of visits by distance to a cancellation and their visit lengths. The sample use corresponds to the final sample as exposed in Table 1. Subfigure 3a shows the proportion of visits which had no previous cancellation (distance 0), a cancellation in the previous visit (distance 1), and so forth. Subfigure 3b displays the unconditional mean of both visit length and expected visit length by the distance to a preceding cancellation.

Figure 4: Differences of performance between physicians

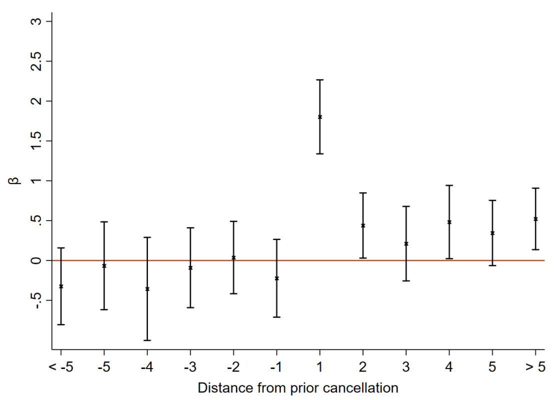


Notes: The figure displays the average of different performance indicators for each physician. *Visit Length* corresponds to every physician's average time reviewing patients. *Cancellations per day* measures every physician's average number of cancellations per working day. *Prob. Prior Cancellation* measures the probability that a given visit had its preceding scheduled visit canceled. *Prob. Testing* identifies every physician's testing probability. *Prob. Drug Prescription* identifies every physician's drug prescription probability. *Prob. Diagnosis* identifies every physician's diagnostic provision rate.

Figure 5: First Stage at Multiple Distances



(a) All shifts



(b) Shifts with one or no cancellation

Notes: The figure reports how cancellations impact surrounding visits. Subfigure 5a uses the final sample as exposed in Table 1, and shows graphically the first stage results using dummy variables identifying those visits at 1, 2, 3, 4, 5, or more than 5 visits from a cancellation. Subfigure 5b uses only those shifts with one or no cancellations, and shows graphically the first stage results using dummy variables identifying those visits at 1, 2, 3, 4, 5, or more than 5 visits from a cancellation, both prior and posterior to a cancellation. The results presented in both figures include all the fixed effects and controls as in our benchmark specification (see Table 3). Confidence intervals at the 95%.

Table 1: Summary Statistics

	Mean	SD	Min	Max	N
Patient characteristics					
Male	0.45	0.50	0	1	67530
Age	58.85	19.55	0	106	67530
Reference BHZ	0.60	0.49	0	1	67530
Distance from hospital (km)	4.37	12.87	0	1979	67530
Born in Spain	0.68	0.47	0	1	67530
Public coverage	0.98	0.12	0	1	67530
Chronic condition	0.06	0.23	0	1	67530
Physician characteristics					
Physician: Male	0.59	0.49	0	1	66350
Physician: Age	49.78	9.32	32	65	58301
Visit characteristics					
Visit length (mins)	12.58	9.59	1	120	67530
Follow-up visit	0.28	0.45	0	1	67530
Out of agenda	0.15	0.35	0	1	67530
Internal referral	0.11	0.32	0	1	67530
Waiting list (days)	29.73	52.02	0	770	67530
Waiting room (mins)	27.22	32.62	0	545	67530
Tests	0.29	0.75	0	15	67530
Test cost	12.67	50.58	0	2019	67530
Drugs	2.04	27.34	0	2600	67530
Diagnosis	0.08	0.27	0	1	67530

Notes: The table provides a summary statistics for our sample of interest. Reference BHZ is an indicator variable that identifies whether the patient comes from a Basic Health Zone covered by the outpatient department. Distance from hospital is a variable that measures how many kilometers apart is the patient's Basic Health Zone centroid from the hospital using a linear distance algorithm. Public coverage is an indicator variable that identifies whether the treated patient is covered by the general public health insurance. Chronic condition is an indicator variable that identifies if the patient previously was been diagnosed any chronic condition. Visit length identifies how long a visit is using the patient's profile opening and closure in the physician's terminal. Out of agenda identifies whether the visit was placed in a slot not covered by the physician's agenda (visit schedule). Internal referral identifies if the visit was appointed by another hospital physician as opposed to a general practitioner. Waiting room is a variable that measures how many minutes has the patient been waiting prior to the visit start. Test cost indicates the testing cost per visit in euros. The variable Drugs captures the number of drugs prescribed measured using the Defined Daily Dose (DDD) definition. Diagnosis is an indicator variable identifying if a visit led to the definition of a precise diagnosis. Physician related variables such as age or sex have missing observations as some physicians preferred not disclosing such information. All other variables are self-explanatory.

Table 2: Covariate Test

	(1) Male	(2) Age	(3) Ref. BHZ	(4) Dist. BHZ	(5) Chronic	(6) Pub. Cov	(7) Spanish	(8) Waiting list	(9) Same sex	(10) Same age
Prior Cancel	-0.0039	0.2213	0.0057	-0.0434	0.0032	0.0003	-0.0052	1.0568	-0.0030	0.0046
	(0.0045)	(0.1812)	(0.0056)	(0.1492)	(0.0023)	(0.0012)	(0.0047)	(0.7029)	(0.0046)	(0.0043)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530	66350	58301
Dep. Var. Mean	0.447	58.85	0.598	4.365	0.0582	0.984	0.677	29.73	0.517	0.152

Notes: The table tests whether having a prior cancellation predicts the patient and the shared physician-patient characteristics. Ref. BHZ is an indicator variable that identifies if the patient comes from a Basic Health Zone covered by the hospital. Dist. BHZ measures how many kilometers apart is the patient's Basic Health zone from the hospital using a linear distance algorithm. Chronic is an indicator variable that identifies if the patient previously had any chronic condition. Pub. Cov. identifies if a visit was covered by the public insurance scheme. Spanish identifies those patients born in Spain. Waiting list measures the days that patients wait to access a first visit from their corresponding Primary Care center. Same sex identifies if both physician and patient share the same sex. Same age identifies if both physician and patient have a similar age, measured using a 10 years window. All other variables are self-explanatory. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effect of Visit Length on Visit Outcomes - Main Analysis

	(1) Length	(2) Diagnosis	(3) Test	(4) Num. Tests	(5) Testing cost	(6) Drug	(7) Num. Drugs	(8) Follow-up
Length		0.0036**	0.0065***	0.0096**	0.8045**	-0.0010	-0.4106*	0.0092***
		(0.0018)	(0.0023)	(0.0042)	(0.3470)	(0.0011)	(0.2166)	(0.0032)
Prior Cancel	1.6222***							
	(0.1598)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	12.58	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280
F - Stat	–	104.3	104.3	104.3	104.3	104.3	104.3	104.3

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effect of Visit Length on Diagnosis Provision

	(1) Diagnosis	(2) Common	(3) Uncommon
Length	0.0036**	0.0001	0.0034**
	(0.0018)	(0.0008)	(0.0014)
Month-Year FE	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	67530	67530	67530
Dep. Var. Mean	0.0819	0.0123	0.0695
F - Stat	104.3	104.3	104.3

Notes: The reported regressions correspond to the 2nd Stage with the following outcomes: i) the probability of a diagnosis (Col. 1), ii) the probability of a common diagnosis (Col. 2), and iii) the probability of an uncommon diagnosis (Col. 3). Diagnoses are classified as common identify those diagnoses most repeated in a given specialization, while uncommon represent any other non modal diagnosis. See Table 3 for further reference on the controls used. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Effect of Current Visit Length on the Next Visit Outcomes

	(1) Length	(2) F. Length	(3) F. Tests	(4) F. Num. Tests	(5) F. Drugs	(6) F. Num. Drugs	(7) Same Physician
Length		0.0953	0.0008	-0.0013	0.0008	0.5331	0.0105***
		(0.1848)	(0.0034)	(0.0055)	(0.0008)	(0.4414)	(0.0037)
Prior Cancel	1.8596***						
	(0.2439)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14350	14350	14350	14350	14350	14350	14350
Dep. Var. Mean	14.39	11.19	0.143	0.195	0.00613	0.552	0.656
F - Stat	–	58.82	58.82	58.82	58.82	58.82	58.82

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-7). The sample used refers to all those visits that had a follow-up visit appointed on that same first visit. The outcomes used refer to the follow-up visit. For information on the outcome variables, please refer to Section 4.1. *Same Physician* is a dummy variable that takes value one if the visit was conducted by the same physician that conducted the first one, and zero otherwise. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. All the controls used are measured as in the first visit. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Effect of Current Visit Length on the Next Visit Cancellation

		Next visit cancelled		
	Length	All	By patient	By physician
	(1)	(2)	(3)	(4)
Length		-0.0001	0.0036	-0.0037**
		(0.0048)	(0.0043)	(0.0018)
Prior Cancel	1.8328***			
	(0.1947)			
Month-Year FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	14.34	0.240	0.211	0.0287
F - Stat	–	89.65	89.65	89.65

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-7). The sample used refers to all those visit that had a follow-up visit appointed on that same visit. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. All the controls used are measured as they were during the first visit. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Effect of Visit Length on Visit Outcomes - By Patient sex

	(1) Length	(2) Length Male	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs
Length			0.0033	0.0081**	0.0107	1.4358***	-0.0019	-0.5883**
			(0.0022)	(0.0034)	(0.0067)	(0.4917)	(0.0019)	(0.2329)
Length × Male			0.0005	-0.0033	-0.0024	-1.3088*	0.0020	0.3682
			(0.0028)	(0.0044)	(0.0088)	(0.7509)	(0.0025)	(0.2928)
Male	-0.0163	12.3993***	-0.0052	0.0315	0.0138	16.6131*	-0.0232	-4.0772
	(0.1029)	(0.5845)	(0.0352)	(0.0565)	(0.1139)	(9.6802)	(0.0313)	(3.6727)
Prior Cancel	1.5313***	0.0901						
	(0.1754)	(0.0844)						
Prior Cancel × Male	0.2067	1.5743***						
	(0.1656)	(0.2835)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Joint Length p-value	–	–	0.0949	0.106	0.120	0.810	0.995	0.446
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	19.15	19.15	19.15	19.15	19.15	19.15

Notes: The reported regressions correspond to the 1st Stage regression (Col. 1-2) and the 2nd Stage with multiple outcome variables (Col. 3-8). The table presents the interaction of *Length* and the patient's sex (*Male*). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length* × *Male*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Effect of Visit Length on Visit Outcomes - By Patient-Physician sex

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Length	Length Male	Diagnosis	Test	Num. Tests	Test Cost	Drug	Num. Drugs
Length			0.0046**	0.0103***	0.0220***	1.4593***	0.0008	-0.3642
			(0.0021)	(0.0036)	(0.0064)	(0.4992)	(0.0016)	(0.2773)
Length × Same sex			-0.0021	-0.0073*	-0.0242***	-1.2207*	-0.0036	-0.0894
			(0.0027)	(0.0044)	(0.0091)	(0.7327)	(0.0026)	(0.2728)
Same sex	-0.0772	12.3465***	0.0292	0.0940*	0.3127***	16.4118*	0.0428	0.6551
	(0.1067)	(0.5926)	(0.0332)	(0.0561)	(0.1161)	(9.2885)	(0.0319)	(3.4255)
Prior Cancel	1.6723***	0.0824						
	(0.1621)	(0.1057)						
Prior Cancel × Same sex	-0.0264	1.4853***						
	(0.1727)	(0.2761)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66350	66350	66350	66350	66350	66350	66350	66350
Joint Length p-value	–	–	0.261	0.288	0.718	0.639	0.116	0.0506
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	17.44	17.44	17.44	17.44	17.44	17.44

Notes: The reported regressions correspond to the 1st Stage regression (Col. 1-2) and the 2nd Stage with multiple outcome variables (Col. 3-8). The table presents the interaction of *Length* and whether the patient and physician have the sex (*Same sex*). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length × Same sex*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Effect of Visit Length on Visit Outcomes - By Nationality

	(1) Length	(2) Length Spanish	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs
Length			0.0044**	0.0054*	0.0095*	0.9784**	-0.0000	-0.5015
			(0.0021)	(0.0030)	(0.0057)	(0.4856)	(0.0014)	(0.3364)
Length × Non-Spanish			-0.0024	0.0031	0.0001	-0.5006	-0.0028	0.2617
			(0.0035)	(0.0059)	(0.0096)	(0.8946)	(0.0042)	(0.4364)
Non-Spanish	0.1674	12.2274***	0.0243	-0.0395	-0.0079	5.6797	0.0300	-3.5730
	(0.1450)	(0.5984)	(0.0465)	(0.0754)	(0.1228)	(11.1152)	(0.0487)	(5.5017)
Prior Cancel	1.6390***	0.0538						
	(0.1748)	(0.0677)						
Prior Cancel × Non-Spanish	-0.0507	1.5372***						
	(0.2392)	(0.2804)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Joint Length p-value	–	–	0.501	0.0629	0.178	0.468	0.392	0.269
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	20.59	20.59	20.59	20.59	20.59	20.59

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). The table presents the interaction of *Length* and whether the patient was born in Spain (*Spanish*). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value refers to the joint significance of *Length* and *Length* × *Spanish*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Effect of Visit Length on Visit Outcomes - By Waiting List

	(1) Length	(2) Length WaitLong	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs
Length			0.0061**	0.0109***	0.0153***	0.7824*	-0.0023	-0.4661**
			(0.0025)	(0.0033)	(0.0058)	(0.4064)	(0.0016)	(0.2311)
Length × WaitLong			-0.0091**	-0.0149**	-0.0191**	0.0976	0.0042	0.1840
			(0.0037)	(0.0061)	(0.0097)	(0.5968)	(0.0035)	(0.2255)
WaitLong	-0.7258**	11.6228***	0.1012**	0.1604**	0.1836	-4.6967	-0.0540	-2.7691
	(0.3084)	(0.5002)	(0.0494)	(0.0768)	(0.1196)	(7.3844)	(0.0408)	(2.8035)
Prior Cancel	1.6671***	0.0187						
	(0.1834)	(0.0498)						
Prior Cancel × WaitLong	-0.1346	1.3745***						
	(0.2117)	(0.2154)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Joint Length p-value	–	–	0.221	0.370	0.593	0.0860	0.432	0.274
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	25.17	25.17	25.17	25.17	25.17	25.17

Notes: The reported regressions correspond to the 1st Stage regression (Col. 1-2) and the 2nd Stage with multiple outcome variables (Col. 3-9). The table presents the interaction of *Length* and whether the patient had to wait more than the average service waiting list (*WaitLong*). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. Joint Length p-value refers to the joint p-value of *Length* and *Length* × *WaitLong*. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Effect of Visit Length on Visit Outcomes - By Specialization Type

	(1) Length	(2) Diagnosis	(3) Tests	(4) Num. Tests	(5) Test Cost	(6) Drugs	(7) Num. Drugs	(8) Follow-up
Panel A: Internal medicine specialization								
Length		0.0055***	0.0060	0.0110**	1.1976**	0.0003	-0.6096	0.0136***
		(0.0015)	(0.0039)	(0.0055)	(0.5922)	(0.0011)	(0.5049)	(0.0034)
Prior Cancel	2.2361***							
	(0.3030)							
Observations	23339	23339	23339	23339	23339	23339	23339	23339
Dep. Var. Mean	15.65	0.0747	0.197	0.278	14.07	0.0295	2.840	0.343
F - Stat	–	55.86	55.86	55.86	55.86	55.86	55.86	55.86
Panel B: Surgical specialization								
Length		0.0022	0.0063**	0.0087	0.4616	-0.0020	-0.2617**	0.0065
		(0.0028)	(0.0028)	(0.0061)	(0.3715)	(0.0016)	(0.1070)	(0.0048)
Prior Cancel	1.3514***							
	(0.1691)							
Observations	44141	44141	44141	44141	44141	44141	44141	44141
Dep. Var. Mean	10.95	0.0857	0.172	0.291	11.94	0.0353	1.624	0.248
F - Stat	–	65.23	65.23	65.23	65.23	65.23	65.23	65.23
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). Panel A includes all observations covering visits that happened in an internal medicine specialization, while Panel B includes those that happened at a surgical specialization. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. The specialties classified as internal medicine are: Allergology, Cardiology, Dermatology, Endocrinology, Internal Medicine, Neurology, Oncology, Pain pathologies, Pulmonology, and Rheumatology; while those specialties classified as surgical are: Cardiovascular surgery, General surgery, Maxillofacial surgery, Ophthalmology, Orthopedics, Otolaryngology, and Urology. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Visit characteristics by Senior Physicians

	(1) Exp. Visit Length	(2) Overbook	(3) Visits/hour	(4) Overloaded day
Senior Physician	-0.2446	-0.0367***	-0.2967***	-0.0829***
	(0.1983)	(0.0115)	(0.0955)	(0.0268)
Month-Year FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes
Observations	58301	58301	58301	58301
Dep. Var. Mean	14.93	0.212	4.255	0.240

Notes: The table tests whether senior physicians, measured as those above the median age in the outpatient department, have different type of visits. Exp. Visit Length is a hospital-provided variable that measures how long a given visit should be. Overbook is an indicator variable that identifies those visits that were appointed on the time slot of a prior visit. Overloaded day is an indicator variable that identifies those days in which the total expected visiting time a physician has, exceeds the time he/she is at the outpatient department. All other variables are self-explanatory. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Patient characteristics by Senior Physicians

	(1) Male	(2) Age	(3) Ref. BHZ	(4) Dist. BHZ	(5) Chronic	(6) Pub. Cov	(7) Spanish	(8) Waiting list
Senior Physician	-0.0115	0.5690	0.0243	-0.0957	-0.0007	-0.0237	0.0099	-3.8768*
	(0.0093)	(0.3451)	(0.0306)	(0.5525)	(0.0027)	(0.0157)	(0.0168)	(2.0910)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58301	58301	58301	58301	58301	58301	58301	58301
Dep. Var. Mean	0.447	58.85	0.598	4.365	0.0582	0.984	0.677	29.73

Notes: The table tests whether senior physicians, measured as those above the median age in the outpatient department, have different type of patients compared to their junior colleagues. Ref. BHZ is an indicator variable that identifies if the patient comes from a Basic Health Zone covered by the hospital. Dist. BHZ measures how many kilometers apart is the patient's Basic Health zone from the hospital using a linear distance algorithm. Chronic is an indicator variable that identifies if the patient previously had any chronic condition. Pub. Cov. identifies if a visit was covered by the public insurance scheme. Spanish identifies those patients born in Spain. Waiting list measures the days that patients wait to access a first visit from their corresponding Primary Care center. All other variables are self-explanatory. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Effect of Visit Length on Visit Outcomes - By Seniority

	(1) Length	(2) Length Senior	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs	(9) Follow-up
Length			0.0073**	0.0068*	0.0130***	1.2940**	-0.0017	-0.6812*	0.0116***
			(0.0030)	(0.0036)	(0.0049)	(0.5066)	(0.0016)	(0.4093)	(0.0044)
Length × Senior			-0.0075*	-0.0029	-0.0071	-1.1112*	0.0009	0.4865	-0.0064
			(0.0042)	(0.0046)	(0.0091)	(0.6618)	(0.0021)	(0.3965)	(0.0060)
Senior	-0.7348***	11.1466***	0.0473	0.0473	0.1047	17.6521**	-0.0135	-6.2473	0.1078
	(0.2682)	(1.0392)	(0.0523)	(0.0558)	(0.1189)	(7.9696)	(0.0239)	(4.9516)	(0.0729)
Prior Cancel	1.7592***	-0.0574**							
	(0.2560)	(0.0274)							
Prior Cancel × Senior	-0.1712	1.7390***							
	(0.3677)	(0.2621)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58301	58301	58301	58301	58301	58301	58301	58301	58301
Joint Length p-value			0.949	0.223	0.443	0.680	0.598	0.0720	0.245
Dep. Var. Mean			0.0763	0.169	0.266	11.97	0.0384	2.363	0.283
F - Stat			22.05	22.05	22.05	22.05	22.05	22.05	22.05

Notes: The reported regressions correspond to the 1st Stages (Col. 1-2), and to the 2nd Stage with multiple outcome variables (Col. 3-8) and visit length interacted by the physician's seniority. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length × Senior*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table 15: Effect of Visit Length on Diagnosis Provision - By Seniority

	(1) Length	(2) Length Senior	(3) Diagnosis	(4) Common	(5) Uncommon
Length			0.0073**	0.0009	0.0064***
			(0.0030)	(0.0014)	(0.0021)
Length × Senior			-0.0075*	-0.0010	-0.0065**
			(0.0042)	(0.0016)	(0.0033)
Senior	-0.7348***	11.1466***	0.0473	-0.0004	0.0476
	(0.2682)	(1.0392)	(0.0523)	(0.0199)	(0.0415)
Prior Cancel	1.7592***	-0.0574**			
	(0.2560)	(0.0274)			
Prior Cancel × Senior	-0.1712	1.7390***			
	(0.3677)	(0.2621)			
Month-Year FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	58301	58301	58301	58301	58301
Joint Length p-value	–	–	0.949	0.945	0.959
Dep. Var. Mean	–	–	0.0763	0.0110	0.0653
F - Stat	–	–	22.05	22.05	22.05

Notes: The reported regressions correspond to the 1st Stages (Col. 1-2), and to the 2nd Stage with the following outcomes: i) the probability of a diagnosis (Col. 3), ii) the probability of a common diagnosis (Col. 4), and iii) the probability of an uncommon diagnosis (Col. 5). Diagnoses are classified as common identify those diagnoses most repeated in a given specialization, while uncommon represent any other non modal diagnosis. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length* × *Senior*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Appendix

A Tables

Table A1: Effect of a Prior Cancellation on Visit Length - Time to End Shift

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	6 Hours	5 Hours	4 Hours	3 Hours	2 Hours	Last Hour	Overtime
	Length	Length	Length	Length	Length	Length	Length
Prior Cancel	2.5271***	1.9414***	1.6238***	1.6337***	1.7079***	0.6215**	-0.3333
	(0.6106)	(0.2728)	(0.2345)	(0.2409)	(0.2304)	(0.2858)	(1.1706)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2014	6558	12031	14323	14687	11964	3862
Dep. Var. Mean	13.44	13.29	12.64	12.64	12.18	12.42	10.92

Notes: The reported regressions correspond to the first stage estimation using *Prior Cancel* as the main regressor. The ending time in a given shift is calculated using appointment times. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Covariate Test - Patient Choice Specializations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Male	Age	Ref. BHZ	Dist. BHZ	Chronic	Pub. Cov	Spanish	Waiting list	Same sex	Same age
Prior Cancel	-0.0037	0.2639	0.0108	-0.2057	0.0038	-0.0003	-0.0051	1.2624	0.0010	0.0088*
	(0.0054)	(0.2226)	(0.0066)	(0.1277)	(0.0032)	(0.0010)	(0.0055)	(0.9336)	(0.0056)	(0.0052)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47832	47832	47832	47832	47832	47832	47832	47832	46652	40682
Dep. Var. Mean	0.465	60.28	0.645	3.812	0.0610	0.991	0.703	31.63	0.526	0.143

Notes: The table tests whether having a prior cancellation predicts the patient and shared physician-patient characteristics, on those specializations in which patients can choose their preferred slot. Ref. BHZ is an indicator variable that identifies if the patient comes from Basic Health Zone covered by the hospital. Dist. BHZ measures how many kilometers apart is the patient's Basic Health zone from the hospital using a linear distance algorithm. Chronic is an indicator variable that identifies if the patient previously had any chronic condition. Pub. Cov. identifies if a visit was covered by the public insurance scheme. Spanish identifies those patients born in Spain. Waiting list measures the days that patients wait to access a first visit from their corresponding Primary Care center. Same sex identifies if both physician and patient share the same sex. Same age identifies if both physician and patient have a similar age, measured using a 10 years window. All other variables are self-explanatory. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Covariate Test - Late Prior Patient

	(1) Male	(2) Age	(3) Ref. BHZ	(4) Dist. BHZ	(5) Chronic	(6) Pub. Cov	(7) Spanish	(8) Waiting list	(9) Same sex	(10) Same age
Prior Cancel	-0.0039	0.2141	0.0060	-0.0497	0.0032	0.0002	-0.0052	1.0555	-0.0032	0.0046
	(0.0045)	(0.1806)	(0.0056)	(0.1495)	(0.0023)	(0.0012)	(0.0047)	(0.7017)	(0.0046)	(0.0042)
Prior Late	0.0009	-0.3156	0.0112	-0.2361***	0.0003	-0.0046**	-0.0016	-0.2962	-0.0096	-0.0011
	(0.0062)	(0.2046)	(0.0068)	(0.0824)	(0.0024)	(0.0020)	(0.0042)	(0.8013)	(0.0059)	(0.0031)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530	66350	58301
Dep. Var. Mean	0.447	58.85	0.598	4.365	0.0582	0.984	0.677	29.73	0.517	0.152

Notes: The table tests whether a late arrival of the previous patient predicts the current patient and shared physician-patient characteristics. Ref. BHZ is an indicator variable that identifies if the patient comes from Basic Health Zone covered by the hospital. Dist. BHZ measures how many kilometers apart is the patient's Basic Health zone from the hospital using a linear distance algorithm. Chronic is an indicator variable that identifies if the patient previously had any chronic condition. Pub. Cov. identifies if a visit was covered by the public insurance scheme. Spanish identifies those patients born in Spain. Waiting list measures the days that patients wait to access a first visit from their corresponding Primary Care center. Same sex identifies if both physician and patient share the same sex. Same age identifies if both physician and patient have a similar age, measured using a 10 years window. All other variables are self-explanatory. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Effect of Visit Length and Delay on Visit Outcomes

	(1) Length	(2) Delay	(3) Diagnosis	(4) Tests	(5) Num. Tests	(6) Test Cost	(7) Drugs	(8) Num. Drugs	(9) Follow-up
Length			0.0036**	0.0062***	0.0095**	0.7484**	-0.0005	-0.3482**	0.0105***
			(0.0017)	(0.0024)	(0.0045)	(0.3344)	(0.0009)	(0.1726)	(0.0032)
Delay			-0.0000	-0.0003	-0.0001	-0.0686	0.0006*	0.0764	0.0016*
			(0.0006)	(0.0006)	(0.0010)	(0.0802)	(0.0003)	(0.0686)	(0.0008)
Prior Cancel	1.6256***	-1.1688**							
	(0.1595)	(0.4783)							
Prior Late	0.1356	6.1898***							
	(0.1120)	(0.6744)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	12.58	16.20	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280
F - Stat	–	–	42.39	42.39	42.39	42.39	42.39	42.39	42.39

Notes: The reported regressions correspond to the two 1st Stages (Col. 1-2), and the 2nd Stage with multiple outcome variables (Col. 3-9). Prior Late is an indicator variable that identifies whether the previous patient arrived to the hospital after her scheduled visit time. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table A3 for the corresponding instrument covariate test. F-Stat corresponds to the first-stage joint F-statistics measure proposed by Kleibergen and Paap (2006). Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Effect of Visit Length on Visit Outcomes - No Controls

	(1) Length	(2) Diagnosis	(3) Test	(4) Num. Tests	(5) Test Cost	(6) Drug	(7) Num. Drugs	(8) Follow-up
Length		0.0021	0.0066***	0.0098**	0.7940**	-0.0012	-0.4193*	0.0093***
		(0.0022)	(0.0023)	(0.0043)	(0.3484)	(0.0011)	(0.2182)	(0.0032)
Prior Cancel	1.6205***							
	(0.1585)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No	No	No
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	12.58	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280
F - Stat	–	105.8	105.8	105.8	105.8	105.8	105.8	105.8

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). For information on the outcome variables, please refer to Section 4.1. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Effect of a Prior Cancellation on Visit Outcomes - ITT

	(1) Diagnosis	(2) Test	(3) Num. Tests	(4) Test Cost	(5) Drug	(6) Num. Drugs	(7) Follow-up
Prior Cancel	0.0058*	0.0105**	0.0155**	1.3050**	-0.0016	-0.6661*	0.0149***
	(0.0029)	(0.0041)	(0.0072)	(0.5999)	(0.0017)	(0.3433)	(0.0052)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280

Notes: The reported regressions correspond to the ITT estimation using *Prior Cancel* as the main regressor. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Effect of Visit Length on Visit Outcomes - OLS

	(1) Diagnosis	(2) Test	(3) Num. Tests	(4) Test cost	(5) Drug	(6) Num. Drugs	(7) Follow-up
Length	0.0011***	0.0012**	0.0029***	0.2017***	0.0003***	0.0210**	0.0034***
	(0.0002)	(0.0005)	(0.0011)	(0.0569)	(0.0001)	(0.0100)	(0.0006)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280

Notes: The reported regressions correspond to the OLS estimation using *Length* as the main regressor. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Effect of Visit Length on Visit Outcomes
Instrumenting with the Number of Previous Cancellations

	(1) Length	(2) Diagnosis	(3) Test	(4) Num. Tests	(5) Test Cost	(6) Drug	(7) Num. Drugs	(8) Follow-up
Length		-0.0017	0.0131***	0.0175**	0.6108*	-0.0023	-0.0514	0.0091*
		(0.0052)	(0.0038)	(0.0068)	(0.3578)	(0.0018)	(0.2078)	(0.0052)
# Previous Cancellations	0.3343***							
	(0.0415)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No	No	No
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	12.58	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280
F - Stat		65.56	65.56	65.56	65.56	65.56	65.56	65.56

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). For information on the outcome variables, please refer to Section 4.1. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Effect of Visit Length on Clinical Process Duration

	(1) Length	(2) Case duration	(3) Length	(4) Case duration
Length		1.1678**		0.6699
		(0.5564)		(0.9142)
Prior Cancel	1.6222***		1.8414***	
	(0.1598)		(0.1961)	
Month-Year FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	67530	67530	18846	18846
Dep. Var. Mean	12.58	30.13	14.36	108
F - Stat	–	104.3	–	89.24

Notes: The reported regressions correspond to the 1st Stage (Col. 1 & 3), and the 2nd Stage (Col. 2 & 4). The variable Case duration measures the number of days, after a first visit, that has taken a clinical process to end. Columns 1 and 2 use the whole sample and provide a value 0 to those first visits that had no follow-up, and Columns 3 and 4 use only those first visits that scheduled a follow-up visit. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Covariate Test - Follow-up Visits

	(1) Male	(2) Age	(3) Ref. BHZ	(4) Dist. BHZ	(5) Chronic	(6) Pub. Cov	(7) Spanish	(8) Waiting list	(9) Same sex	(10) Same age
Prior Cancel	-0.0071	0.2368	0.0158	0.2433	0.0045	0.0031	-0.0226**	1.9820	0.0043	0.0072
	(0.0096)	(0.4141)	(0.0113)	(0.3040)	(0.0051)	(0.0023)	(0.0108)	(1.2038)	(0.0095)	(0.0087)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14350	14350	14350	14350	14350	14350	14350	14350	14266	12530
Dep. Var. Mean	0.432	62.16	0.663	4.078	0.0702	0.977	0.696	27.09	0.523	0.134

Notes: The table tests whether having a prior cancellation predicts the patient and the shared physician-patient characteristics in a sample of visits with a follow-up appointments. Ref. BHZ is an indicator variable that identifies if the patient comes from a Basic Health Zone covered by the hospital. Dist. BHZ measures how many kilometers apart is the patient's Basic Health zone from the hospital using a linear distance algorithm. Chronic is an indicator variable that identifies if the patient previously had any chronic condition. Pub. Cov. identifies if a visit was covered by the public insurance scheme. Spanish identifies those patients born in Spain. Waiting list measures the days that patients wait to access a first visit from their corresponding Primary Care center. Same sex identifies if both physician and patient share the same sex. Same age identifies if both physician and patient have a similar age, measured using a 10 years window. All other variables are self-explanatory. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A11: Effect of Visit Length on Visit Outcomes - By Retired Patients

	(1) Length	(2) Length Retired	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs
Length			0.0035	0.0043	0.0107	0.7382	-0.0010	-0.4595*
			(0.0029)	(0.0031)	(0.0066)	(0.4982)	(0.0013)	(0.2470)
Length × Retired			0.0000	0.0051	-0.0019	0.1852	-0.0001	0.1144
			(0.0043)	(0.0053)	(0.0095)	(0.7283)	(0.0016)	(0.2279)
Retired	0.2615	12.6102***	-0.0057	-0.0886	-0.0202	-5.4413	0.0006	-1.4926
	(0.1708)	(0.5866)	(0.0569)	(0.0661)	(0.1227)	(9.4129)	(0.0207)	(3.0157)
Prior Cancel	1.5211***	-0.0264						
	(0.1618)	(0.0627)						
Prior Cancel × Retired	0.2585	1.7836***						
	(0.1876)	(0.2516)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Joint Length p-value	–	–	0.177	0.0180	0.144	0.0683	0.413	0.142
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	27.58	27.58	27.58	27.58	27.58	27.58

Notes: The reported regressions correspond to the 1st Stage regression (Col. 1-2) and the 2nd Stage with multiple outcome variables (Col. 3-8). The table presents the interaction of *Length* and whether the patient's age is over 65 (*Retired*). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length* × *Retired*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table A12: Effect of Visit Length on Visit Outcomes - By Shock Type

	(1) Length	(2) Diagnosis	(3) Tests	(4) Num. Tests	(5) Test Cost	(6) Drugs	(7) Num. Drugs	(8) Follow-up
Panel A: No-Show								
Length		0.0036**	0.0078***	0.0111**	0.7637*	-0.0010	-0.3939*	0.0084***
		(0.0018)	(0.0027)	(0.0047)	(0.3910)	(0.0010)	(0.2106)	(0.0032)
Prior No-Show	1.6082***							
	(0.1594)							
Observations	66320	66320	66320	66320	66320	66320	66320	66320
Dep. Var. Mean	12.53	0.0817	0.181	0.286	12.63	0.0332	2.055	0.280
F - Stat	–	103	103	103	103	103	103	103
Panel B: Notification								
Length		0.0037	-0.0036	-0.0022	1.1875	-0.0011	-0.5477	0.0149
		(0.0046)	(0.0058)	(0.0097)	(0.8695)	(0.0027)	(0.3340)	(0.0091)
Prior Notification	1.7260***							
	(0.2885)							
Observations	57702	57702	57702	57702	57702	57702	57702	57702
Dep. Var. Mean	12.39	0.0816	0.180	0.286	12.59	0.0319	2.055	0.279
F - Stat	–	36.20	36.20	36.20	36.20	36.20	36.20	36.20
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). Panel A includes all observations, but those with a prior withdrawal, while Panel B includes all observations, but those with a prior no show up. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Effect of Visit Length on Visit Outcomes - By Overloaded Days

	(1) Length	(2) Length Non Overload	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs
Length			0.0043	0.0099*	0.0132*	0.9296	-0.0015	-0.5138*
			(0.0027)	(0.0054)	(0.0079)	(0.5892)	(0.0030)	(0.2643)
Length × Non Overload			-0.0011	-0.0052	-0.0054	-0.1730	0.0007	0.1523
			(0.0037)	(0.0059)	(0.0099)	(0.7140)	(0.0033)	(0.2747)
Non Overload	0.6932***	12.0272***	0.0042	0.0458	0.0549	2.9035	-0.0115	-1.6484
	(0.1776)	(0.5285)	(0.0461)	(0.0715)	(0.1144)	(8.5425)	(0.0393)	(3.3703)
Prior Cancel	1.9344***	0.0763						
	(0.2555)	(0.0887)						
Prior Cancel × Non Overload	-0.4097	1.4005***						
	(0.2570)	(0.2099)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Joint Length p-value	–	–	0.184	0.0406	0.140	0.0699	0.434	0.136
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	27.58	27.58	27.58	27.58	27.58	27.58

Notes: The reported regressions correspond to the 1st Stage regression (Col. 1-2) and the 2nd Stage with multiple outcome variables (Col. 3-8). The table presents the interaction of *Length* and whether the physician had a non-pressing day (*Non Overload*). The variable *Non Overload* identifies those days in which the total expected visit length exceeds the physician's daily schedule. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length* × *Retired*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table A14: Effect of Visit Length on Visit Outcomes - By High-Performing Physicians

	(1) Length	(2) Length High-Performing	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs
Length			0.0023	0.0056**	0.0116**	0.7769**	-0.0003	-0.3945
			(0.0016)	(0.0025)	(0.0053)	(0.3669)	(0.0008)	(0.2833)
Length × High-Performing			0.0041	0.0026	-0.0064	0.0846	-0.0021	-0.0510
			(0.0048)	(0.0052)	(0.0084)	(0.7778)	(0.0026)	(0.3128)
High-Performing	-1.2899	9.3470***	-0.1316**	-0.1999**	-0.2265	-15.6842	0.0448	1.6781
	(1.6542)	(1.8655)	(0.0540)	(0.0800)	(0.1508)	(9.5695)	(0.0435)	(4.8503)
Prior Cancel	1.8436***	-0.0519***						
	(0.2197)	(0.0195)						
Prior Cancel × High-Performing	-0.5610*	1.4276***						
	(0.3258)	(0.2391)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Joint Length p-value	–	–	0.156	0.0810	0.434	0.225	0.350	0.0280
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	18.13	18.13	18.13	18.13	18.13	18.13

Notes: The reported regressions correspond to the 1st Stage regression (Col. 1-2) and the 2nd Stage with multiple outcome variables (Col. 3-8). The table presents the interaction of *Length* and whether the physician's average time used to provide a diagnosis is lower than the average time used in her specialization (*High-Performing*). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length* × *Retired*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table A15: Effect of Visit Length on Visit Outcomes - By Seniority (1st vs. 4th. Quantile)

	(1) Length	(2) Length Senior	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs	(9) Follow-up
Length			0.0058**	0.0053	0.0101	0.8234	-0.0045*	-0.3879	0.0216**
			(0.0030)	(0.0043)	(0.0075)	(0.7038)	(0.0025)	(0.3418)	(0.0091)
Length × Senior			-0.0083*	-0.0041	-0.0039	-0.3824	0.0034	0.3072	-0.0173*
			(0.0046)	(0.0050)	(0.0121)	(1.0123)	(0.0033)	(0.3806)	(0.0103)
Senior	0.8705	13.8849***	0.0868	0.0322	0.0323	4.1249	-0.0563	-5.0421	0.1903
	(0.9317)	(0.9744)	(0.0629)	(0.0768)	(0.1706)	(14.9792)	(0.0444)	(5.2682)	(0.1397)
Prior Cancel	1.3518***	-0.0629							
	(0.3211)	(0.0901)							
Prior Cancel × Senior	0.9470*	2.3268***							
	(0.5381)	(0.4270)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58301	58301	58301	58301	58301	58301	58301	58301	58301
Joint Length p-value	–	–	0.449	0.607	0.498	0.518	0.646	0.542	0.374
Dep. Var. Mean	–	–	0.0780	0.161	0.250	10.85	0.0424	2.166	0.288
F - Stat	–	–	9.475	9.475	9.475	9.475	9.475	9.475	9.475

Notes: The reported regressions correspond to the 1st Stages (Col. 1-2), and to the 2nd Stage with multiple outcome variables (Col. 3-8) and visit length interacted by the physician's seniority. The sample used corresponds to those physicians in the 1st and 4th quantile of their age distribution. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length* × *Senior*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.